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Detection of Diabetic Retinopathy in Retinal Image Early Identification using Deep CNN

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ABSTRACT

Diabetic Retinopathy, the most common reason of vision loss, is caused by damage to the small blood vessels in the retina. If untreated, it may result in varying degrees of vision loss and even blindness. Since Diabetic Retinopathy is a silent disease that may cause no symptoms or only mild vision problems, annual eye exams are crucial for early detection to improve the chances of effective treatment where fundus cameras are used to capture the retinal images. However, fundus cameras are too big and heavy to be transported easily and too costly to be purchased by every health clinic, so fundus cameras are an inconvenient tool for widespread screening. Recent technological developments have enabled using smartphones in designing small-sized, low-power, and affordable retinal imaging systems to perform Diabetic Retinopathy screening and automated Diabetic Retinopathy detection using machine learning and image processing methods. However, Diabetic Retinopathy detection accuracy depends on the image quality and it is negatively affected by several factors such as Field of View. Since smartphone-based retinal imaging systems have much more compact designs than the traditional fundus cameras, the retina images captured are likely to be low quality with smaller Field of View As a result, the smartphone-based retina imaging systems can be used as an alternative to the direct ophthalmoscope once it tested in the clinical settings. However, the Field of View of the smartphone-based retina imaging systems plays an important role in determining the automatic Diabetic Retinopathy detection accuracy.

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I. INTRODUCTION:

Damage to the retina caused by diabetes is referred to as diabetic nephropathy and is one of the main vision problems. Vision is severely distorted as a result of damage to blood vessels within the retina, which causes fluid leaking and blindness. There are typically four phases of DR,

The first stage is moderate non - proliferative retina when only aneurysms can develop. The blood vessels in the second phase of moderate non-proliferative blindness become so distorted and swollen that they can no longer effectively convey blood.

The next phase is Moderate semi-retinal, which resulted in starved blood flow to the retina due to the increasing obstruction of more vascular systems prompting the retina can encourage the development formation of blood vessels. Proliferative diabetic retinopathy, the ultimate period, occurs when the retina's growth characteristics are released into the vitreous gel that fills the eye and stimulates the creation ofnew blood vessels along the retina's inner layer.

There are distinguishing features and qualities associatedwith each stage. But physicians maybe may well not take anyof them into account, resulting in an incorrect diagnosis as a result, the notion of designing an integrative framework for DR identification is developed. If DR advances through the worst form, it might cause total blindness. About 2.6% of allcases of blindness are due to DR. Patients with diabetes who have had the condition for a long time are more likely to have DR. Diabetic individuals should have routine

retinal exams to detect and treat DR early and reduce the possibility of impairment DR is distinguished by the appearance of various types of anomalies in retinal images. Microaneurysms, hemorrhages and both soft and tough exudates (EX) are all possible, and other lesions fall under this category.

Due to the fragility of the vessel walls, the initial symptom of DR is the appearance of tiny red spots called microaneurysms (MA) on the retina. Sharp edges and a dimension of fewer than 125 m characterize this phenomenon. Figure 1 displays the classification of MA into six subtypes by Michael et al., based on their visibility in AOSLO reflectance and traditional fluorescence imaging.

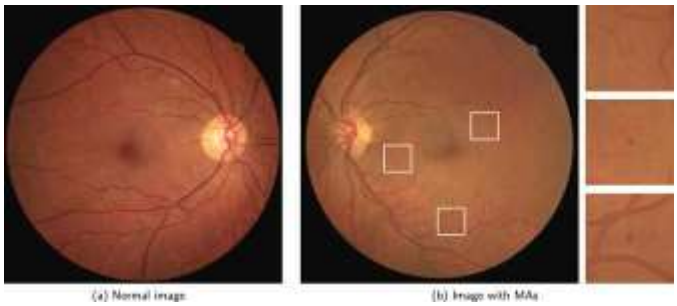

Fig. 1.Normal Vs microaneurysms Image

Patches on the retina that are bigger than 125 m and have an uneven border are considered hemorrhages (HM). Figure 2 depicts the two different forms HMs, which are either referred to as "flame" (superficial HM) in addition to "blot" (deeper HM).

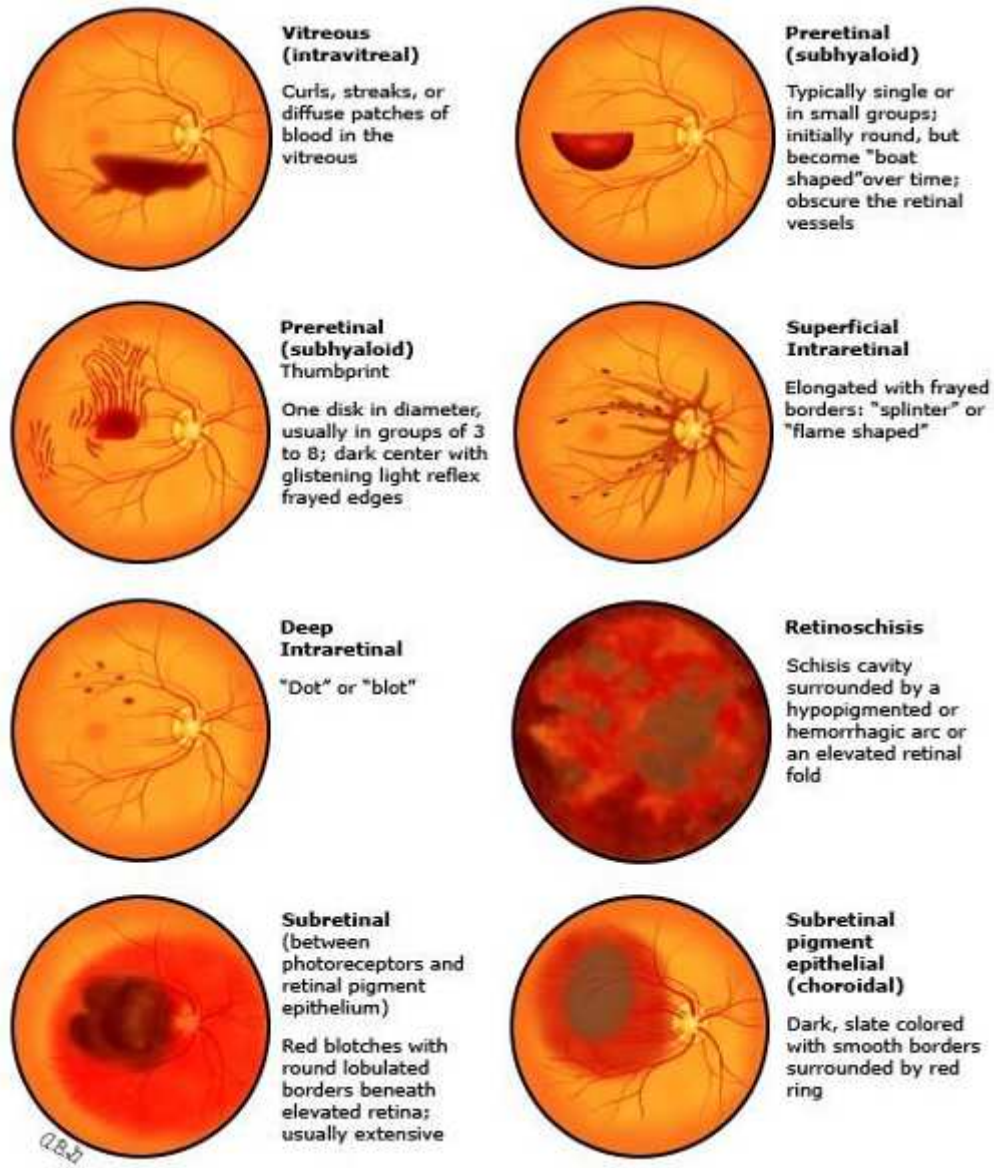

Fig. 2.Types of Microaneurysms

Hard exudates cause vivid yellow areas on the retina owing to blood leaking. They have sharp edges and are positioned in the outer retina.

The expansion of the neuronal cell results in the formation of white regions on the retina known as soft secretions (or cotton wool). The shape might be round or oval.

MA and HM are red lesions, while brilliant lesions are soft and difficult exudates (EX). It provides a concise summary of the five phases Defined as the presence of such lesions, there are five types of DR: no DR, mild DR, intermediate DR, extreme DR, and proliferating DR. Images from each of the DR phases are shown as an example in Figure 3.

Automated approaches for DR diagnosis are far more effective than human diagnostic and may save both time and money. Misdiagnosis is more common with a manual diagnosis, and it takes more time and effort to complete.

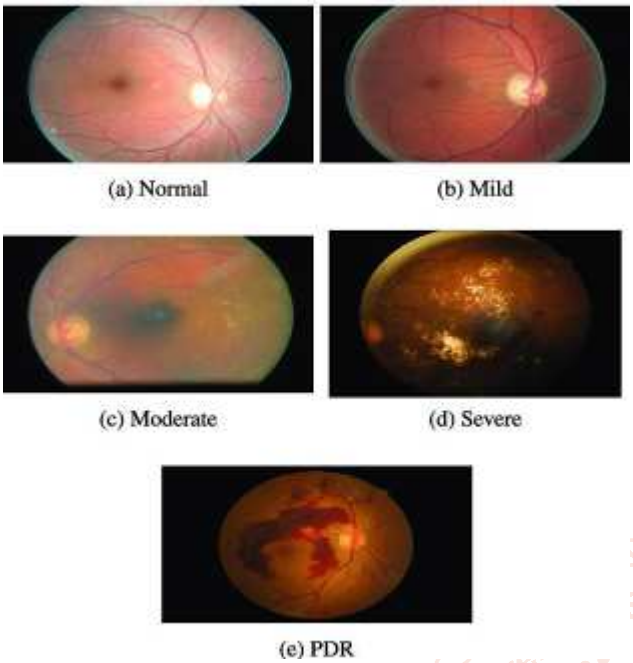

Fig. 3.Types of Hemorrhage [16]

II. LITERATURE SURVEY

The design and Development of a Novel Blood Vessel Identification System Regarding Earlier Detection of Diabetic Retinopathy is the topic of a study presented by Sumeet Dua. In this article, we provide a unique approach for evaluating retinal images that rely on the localized recurrent hierarchical decomposition attained by using quadtrees and edge thread to find blood vessels. Blood vessels are depicted by central and/or cingulate blurring boundaries, which are distinguished by a noticeable brightness difference. This feature also significantly aids in reducing false alarms. The approach reduces the amount of incorrectly discarded edges that are massively essential while being faster than the present way and using less space for the edge map [1].

Many individuals across the globe suffer from diabetic retinopathy, which may lead to blindness. Diabetes mellitus is a dangerous disorder, and prompt treatment for patients depends entirely on an accurate early diagnosis. See Collectively interpretable for the article. Ensemble A deep learning model has been created by researchers to categorize diabetic retinopathy. To reduce the bias generated by anyone deep learning model, the Adaboost approach is also used to aggregate many deep learning models. The methodologies proposed in this study are more stable and ultimately produce better performance compared to standalone deep learning models. The results of the trial supported the advantages of the recommended approach [2].

Diabetic retinopathy (DR), the far more common eye ailment in diabetics, is caused by tiny vascular capillaries in the retina is damaged. Patients with diabetes for 10 years or more are at higher risk for both vision loss and diabetes. The main focus of Diagnostics of Eye Disease is the automatic detection of diabetic retinopathy. Utilizing Morphology Processes and SVM Classifier, which assesses the presence or absence of metabolic byproducts in color fundus retinal images to assess the severity of lesions. The focus of this study is exudates since they identify early indications of diabetic retinopathy. Exudates are mostly brought on by proteins and lipids that seep into the retina from the bloodstream as a result of blood vessel damage. Thus, utilizing a morphological process, we offer an automated technique in this work for exudate detection in non-dilated fundus image retinal photographs. The recommended method allowed these exudates to be distinguished from the retinal image and blood vessels. This study not only defines the disorder but also offers some insight into how severe the illness is. The information supplied by the classifier algorithm helps to provide a more accurate assessment of diabetic retinopathy [3].

Deep learning on fundus images has made automated monitoring and identification of severe diabetic retinopathy a practical and affordable alternative (DR). It has been shown that using an entropy image of the brightness of fundus pictures may help convolutional neural networks (DCNN) based systems identify referable DR more accurately. The paper Identification of Diabetic Retinopathy Using Bichannel Convolutional Neural Networks suggests the entropy image computed using the green component of the retina snapshot. Unsharp masking (UM) is further employed as a pretreatment before the calculation of the probability pictures. In addition to using the properties of both the gray level entropy images and the greenish component produced outcomes by UM, DCNN transfer learning will be employed to enhance the detection skills of attributable DR. One of the main advantages of utilizing a deep learning system is the improvement in accuracy in recognizing and diagnosing diabetic retinopathy. The suggested method, which makes use of deep learning to assist eye physicians in making attributable DR diagnoses, begins with the green channel of the RGB image and would be helpful to the automated retina image analysis system [4].

Diabetic retinopathy, a disorder in which the blood vessels of the retina are damaged, may cause vision loss. Since there is presently no cure for this disorder, it is critical to identify retinal damage early by utilizing a screening technique. According to the

reference [5], segmentation techniques may be used to identify blood vessels, exudates, and microaneurysms in diabetic retinopathy. Performance metrics include things like sensitivity and specificity. The research on Diabetic Retinopathy Detection Accuracy produced encouraging results. Using the One rule and backward propagation neural networks, diabetic and non-diabetic digital retinal fundus images are divided into two categories. This method utilizes a higher number of attributes available compared to previous methods published in the literature by splitting the retinal fundus image into four equal sections. The proposed approach uses the Haar wavelet transform followed by principal component analysis to effectively select features. Results on the DIARETDB1 database demonstrate its suitability, exceeding earlier approaches [6] with a reliability score of 93.8% for a deep recurrent neural network and a score of 97.75% for a specific rule classification.

Amol Prataprao Bhatkar's study focuses on the identification of diabetic retinopathy in retinal pictures, and he uses a Multilayer Perceptron Network (MLPNN) to do this. A technique for automatically assessing whether a retinal image is normal or pathological is provided by the MLPNN classifier. A feature vector with various 09 statistical qualities, including Entropy, mean, standard deviation, average, Euler number, contrast, correlation, energy, and homogeneity, is produced using the 64-point Discrete Cosine Transform (DCT). The MLPNN was used to select the best-quality subset using a training dataset. This work suggests using the MLPNN classifier approach to detect diabetes mellitus in retinal images. Several properties are extracted from retinal images and used as classifier parameters [7]. The 64-point DCT and 9 statistical parameters are some of these characteristics.

Together, references [8] established an innovative technique for DR early detection via the intricately described fractal dimension architecture. For diabetics who are not proliferating at an early stage, the evaluation of Macular Optical Coherence imaging derived from optical coherence tomography angiography (OCTA) scans is helpful. using the Support Vector Machine (SVM) algorithm, a machine learning method under supervision, to automate the diagnostic procedure and increase its accuracy. The categorizing approach now has a 99.5% accuracy rate. In addition to the various stages of diabetic retinopathy, other retinal diseases that affect the distribution of arteries or neovascularization may be categorized using this approach. This work emphasizes the need for the creation of an automated system for categorizing NPDR retinal pictures [9]. Additionally, according to this roadmap, analyzing the skeleton may be a viable method of obtaining certain fractal characteristics, such as the need to account for informational and correlational factors when determining whether a gap exists and when a branching moment occurs. Additionally, the value for the derived multifractals has just been released. A support vector machine gives us a simple computational recipe that produces accurate early diabetic retinopathy diagnosis [10].

A suggested AI-based approach for the early detection of diabetic retinopathy uses picture data to detect and classify diabetic retinopathy. This approach uses machine learning to identify and categorize diabetes mellitus in retinal fundus data as Normal, Moderate, or Proliferative Diabetic Retinopathy (PDR), all of which are helpful diagnostic and therapeutic indicators for treating patients [11]. The approach primarily focuses on binary classification. The recommended method is intended to categorize fundus images into two categories: healthy and diseased. The system is built on the Keras Library and Tensorflow's backend. After the images were processed, the classification algorithm's performance significantly improved. Transfer learning and dynamic learning rate reduction dependent on validation accuracy are used to increase the model's accuracy [12]. All Survey work merits and demerits are displayed in Table 1.

TABLE I. LITERATURE SURVEY - MERIT AND DEMERITS

Merits	Demerits
Without any human oversight, it automatically recognizes crucial features.	It requires more time to train than a typical DCNN.
It also does well while trying to recognize images.	More training data are needed than with some other approaches.
Regarding input size, they are not constrained.	The cost of computation is significant, and complicated data training can be tedious.
less loss of spatial information	It requires a lot of processing power, especially if there are several images.
Preprocessing an image can improve visual contrast and density while also removing noise.	There is no probabilistic basis for the classification because the support vector classifier places data points above and below the classifying hyperplane.

III. PROPOSED APPROACH

DCNN there is already an SVM classifier that makes use of a Machine Learning Algorithm. Normal and glaucomatous retinal pictures from open-source databases, together with information from local hospital databases, have been put intothe program, and the statistical findings have been analyzed. Knowing how to read and save pictures on computers is crucial. The retinal picture may be recognized by a computer down to the pixel level. Figure 4 Class has been trained on both abnormal and normal visions (example 300 images). Brightness and contrast changes to the retina images are made before it is displayed [13]. The term "feature extraction" refers to the process of extracting meta-level characteristics of a picture, (Exchangeable image file formatis called metadata the python code mention to “meta” keyword) such as its geometry, color palette, and degree of contrast. When utilized to selectively enhance the diagnostic system's accuracy, improving healthcare data collection and usage is necessary to increase diagnosis accuracy. Data must support complicated healthcare choices and be of high quality, accurate, and individualization to the patient. it is a powerful tool. The procedure for creating a training picture is identical to that used to create a testing image. Checking the training picture after the input image. Healthy and aberrant Retinal pictures may be predicted using providing well in the machine's next classification DCNN [14]. The primary goal of the 11 recorded image preprocessing is to carefully eliminate duplication without negatively impacting the characteristics that play a crucial part in the process. Converting a picture to grayscale is the input.

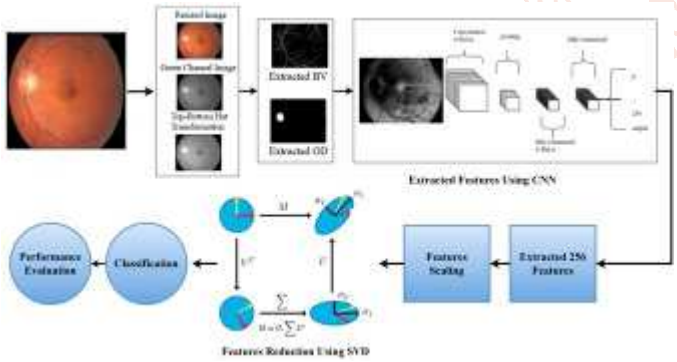

Fig. 4.Proposed Diagram

A. Feature Extraction

Using GLCM for proposed feature parameters is shown in Table 2.

TABLE II PROPOSED FEATURE PARAMETERS

Parameter	40%	60%	DISC
Entropy	8.64	7.97	0.080
Prominence	2.34×10^{7}	1.99×10^{7}	0.159
Correlation	6.47	7.65	0.166
Variance	856	700	0.200
Shade	117000	888	0.274
Homogeneity	0.107	0.157	0.378
IDM	0.0480	0.0842	0.547
Contrast	968	544	0.560
ASM	2.60×10^{-4}	7.20×10^{-4}	0.939

B. DCNN Architecture

Multiple architectures, with a 22-layer deep model being the primary emphasis, were trained and evaluated to determine the efficacy of DCNNs. Utilizing a combination of close-to-the-bottom embeddings and diverse-sized spatial filters, this highly effective network delivers state-of-the-art accuracy. Deeper characteristics may be learned by the network thanks to more convolution layers and better use of its computational power [15].

In a layered architecture shown figure 5, the first layer may be responsible for learning about edges, while the last layer would learn how to understand hard exudate, a characteristic used for DR classification. Each convolution layer in the network is followed by a batch normalization layer to smooth out any spikes in the data caused by the activation at the top layer, which specifies complicated conceived as a way amongst inputs and response variables.

When more feature maps are needed, one batch normalizingper block is implemented.

The DCNN layers are detailed below shown in figure 6 isdescribed.

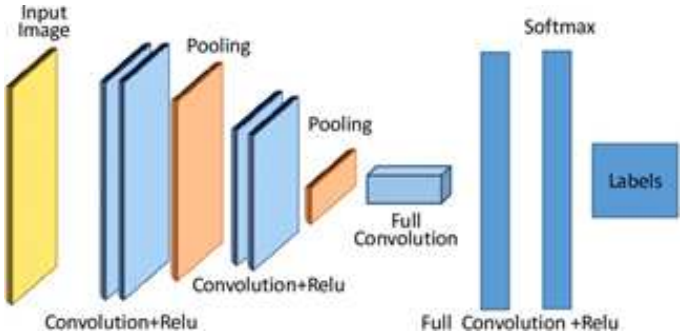

Fig. 5.DCNN Architecture [17]

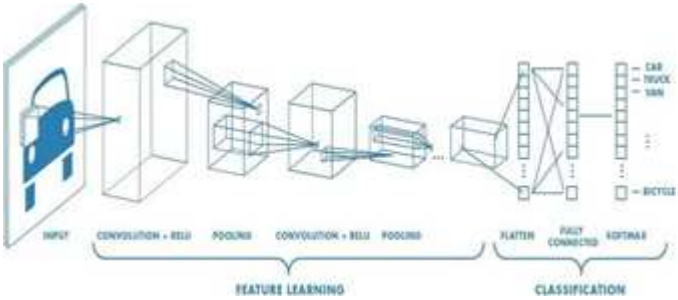

Fig. 6.DCNN Layers

C. Input Layer

For a DCNN to work, the input picture must already have some kind of image data. As we saw before, a three- dimensional matrix is used to represent image data. Make one long column out of it. If your picture has the dimensions2828 = 784, you'll need to multiply it by 1 to get a size suitable for input. Input dimension equals the number of training instances multiplied by m. (784, m).

D. Convolution Layer

Two-dimensional convolution is used to process the inputs. Cross-channel integration of the "dot products" of weights and inputs. Receptive fields may share the same filter weights. The quantity of information includes the same "quality" as the collection of variables, which is the same as the number of channels in the input volume.

E. Pooling Layer

We get activation maps from convolutional layers, then apooling layer aggressively downsamples those activation maps (discarding information in the process), and finally, we employ smaller filters and stop pooling altogether.

F. Fully Connected Layer

Think of it as the last step in the learning process, whereby retrieved visual characteristics are mapped to the intended outcomes. Typically, they adapt to the demands of encoding and classifying data. The most often seen form of output is vectors, which itself is subsequently fed into Softmax to be used as a representation of classification confidence. The neuronal network and brain imaging both play a role in a fully linked layer. It bridges the gap between different layers of neurons. Images may be trained into numerous categories using this method.

G. Softmax Layer

A convolutional neural network's last layer is called the Softmax or Logistic layer. The FC layer it belongs to ends there. Binary classification can be handled by logistics, whereas multi-classification can be handled by softmax. The labeled brain picture is sent to the output layer as a single-hotrepresentation. You should be familiar with DCNN now.

IV. RESULTS AND ANALYSIS

Keras is a Python framework that provides a high-level API for neural networks that can run atop Tensor Flow, Scikit-learn, or Theano. Fast experimentation was a primary design goal throughout development Figures 7 to 14 all are current research work outputs.

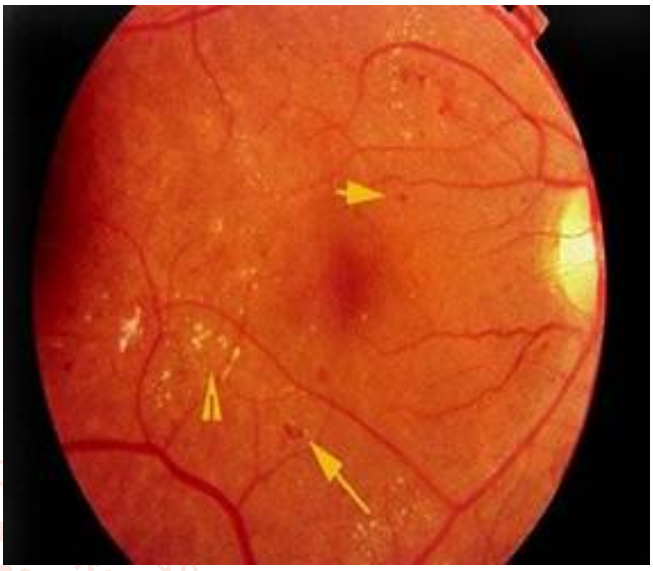

Fig. 7.Input Image

Fig. 8.Pre-processed Image

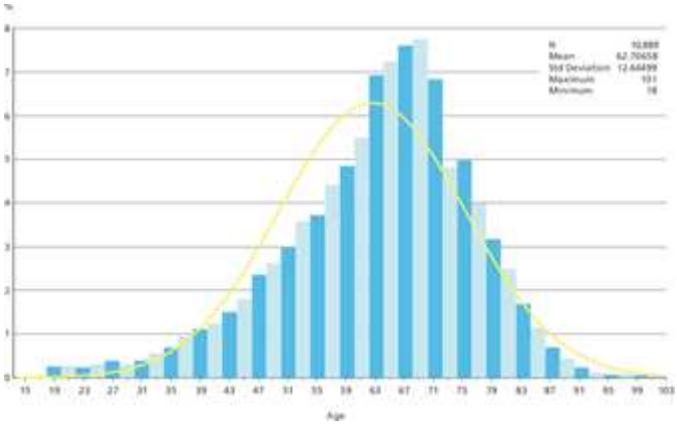

Fig. 9.Histogram for Disease Prediction

Layer (type)	Output Shape	Param #
conv2d_11 (Conv2D)	(None, 62, 62, 32)	896
max_pooling2d_6 (MaxPooling2	(None, 31, 31, 32)	0
conv2d_12 (Conv2D)	(None, 29, 29, 64)	18496
global_average_pooling2d_6 (	(None, 64)	0
dense_11 (Dense)	(None, 128)	8320
dense_12 (Dense)	(None, 1)	129

Total params: 27,841
Trainable params: 27,841
Non-trainable params: 0

Fig. 10. Conv2D Parameter

Fig. 11. Epochs

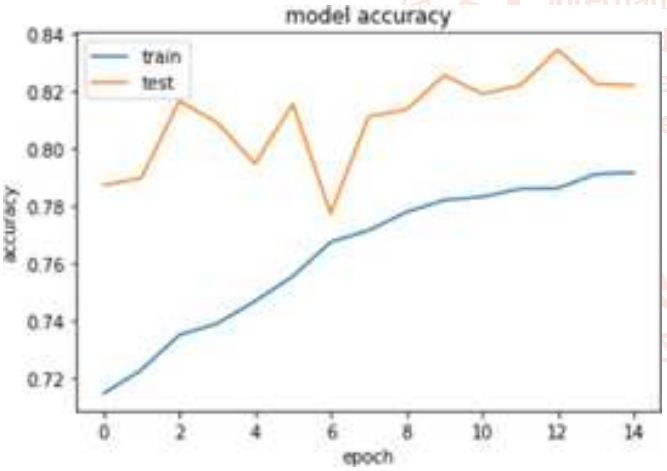

Fig. 12. Model Accuracy

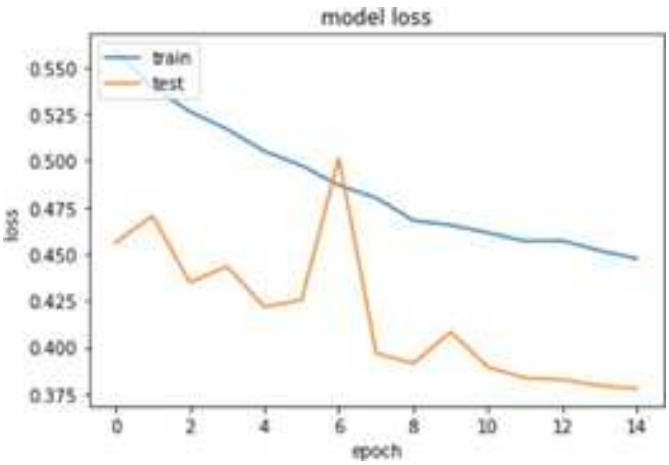

Fig. 13. Model Loss

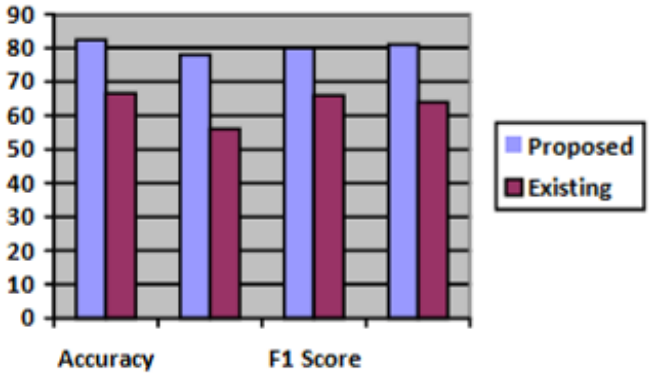

Fig. 14. Comparative Analysis for Existing Vs Proposed

To test our suggested model with this new dataset, we use some algorithms built into the Jupyter notebook. The data as a whole demonstrate the proposed model's suitability for DR prediction using this new dataset shown in Figures 12 and 13. Sensitivity (SN), specificity (SP), and accuracy (ACC) were utilized in this investigation, and true positive (TP) refers to the total number of positively detected samples in the positive set. The number of classification- negative samples in the negative set is referred to as true negative (TP). The number of recognized positive samples in the negative group is known as a false positive (FP). The number of recognized negative samples in the positive set is represented by the term false negative (FN). It is frequently employed to assess the caliber of classification models. The percentage of samples that the classifier successfully classifies to the total number of samples is known as the accuracy. According to the total number of samples, the classifier successfully categorized. Sensitivity and specificity are the two fundamental properties of medical statistics. The true positive rate is sensitivity, and the true negative rate is specificity.

V. CONCLUSION AND FUTURE WORK

Using deep learning on fundus photos, this study effectively diagnoses diabetes, and may one day be utilized as a means for making such a diagnosis. The promise of convolutional neural networks (DCNNs) is that they can understand from raw pixels and so make use of the massive volumes of pictures that have been processed for human- interpreted screening. DCNNs may be able to identify other illnesses thanks to the large heterogeneity and moderate bias of these models. If you look at visualization discover that the indicators used for classification are situated in a section of the characteristics learned by DCNNs. Data is easily discernible to the naked eye. Images of the retina in moderate and severe cases of diabetes include macroscopic characteristics at a scale that is above the capabilities of existing DCNN designs, both for

training and validation. A larger amount of processed data may be used to train the model using the system in the future, yielding more accurateresults. There is an increasing number of people accompanying type 2 diabetes, raising the risk of bleeding such as retinopathy. An estimated 35% of the 285 million individuals worldwide who have diabetes also have diabetic retinopathy, with another 30% of those cases (about 3.2 million people) being severe enough to jeopardize sight.

These days, computer-aided methods for the diagnosis of diabetic retinopathy rely heavily on image-processing techniques that make use of deep learning. Some potential courses of action might improve the efficiency with which deep learning methods are used. However, ophthalmologists are required for the examination and characterization of image data. Most data analysis work has been carried out viathe use of neural network convolutional models to compound growth multi-layer foundations for the diagnostic test of macular degeneration using cloud-based retinal fundus images. As a result of developments in diabetic and blood pressure management, as well as laser treatment and intraocular medication administration, the likelihood of visual impairment from macular degeneration has decreased considerably during the last three decades. However,diabetes continues to be a leading factor in visual impairment. This report reviews the current knowledge on diabetic retinopathy and discusses potential avenues for further study.

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